The Investigation of Impact of Extreme Weather Events on Property Insurance

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Abstract. As the frequency of extreme weather in the world increases, so does the impact on the insurance industry, making the study of extreme weather on the sustainability of insurance properties particularly important. First, it collected some data on extreme weather occurrences from official databases in the United States and Africa. Subsequently, this study chose the SARIMA model to predict the losses and the number of insured people for the next seven years based on the characteristics of the data, and initially determined the baseline factors for the insurance program based on the break-even estimation model this study constructed. Second, this study analyzed the data to determine high-risk areas. Then evaluated the average damage to these high-risk areas from different weather extremes, identified that these extremes occurred most frequently in June. From the above conditions, this article used ArcGis to build a digital elevation model in Florida to select the recommended site areas. Third, in order to determine which buildings in the community should be protected in what way, this article constructed a key educational area scoring model (CGDAM-WRIR) based on the AHP-TOSIS evaluation model, which takes five metrics to derive a risk score and at the end calculates a building score in order to quantify the level of risk. Finally, this study went through a time trend analysis to examine when the different weather extremes occurred with the highest frequency and ranked the average damages of the different extremes to come up with a total event impact analysis.

Keywords: Extreme weather; Insurance; AHP-TOSIS; SARIMA; ArcGIS.

1 Introduction

Climate change represents the most significant risk multiplier confronting the world today. With the increasing frequency and intensity of extreme weather events worldwide, there is a significant impact on the biosphere as well [1, 2]. In this case, the impact on the insurance industry is also intensifying, making it particularly important to study the effects of extreme weather on the sustainability of insurance properties. Therefore, determining how best to adjust property insurance to ensure the system's resilience to future claims costs while maintaining the long-term health of insurance companies has become a key focus area.

As an indispensable part of the global ecosystem, the impact of climate change on

Y. Wang (ed.), *Proceedings of the 2024 2nd International Conference on Image, Algorithms and Artificial Intelligence (ICIAAI 2024)*, Advances in Computer Science Research 115,
https://doi.org/10.2991/978-94-6463-540-9_26

the insurance industry is quite far-reaching [3].

Some related studies have been carried out in the last decade such as the study on weather index insurance design based on the Copula method (using Jiamusi as an example) [4]. However, their proposed method primarily addresses agricultural concerns. As a matter of fact, the insurance industry pressures arising from extreme weather's impact on urban damages, which covers areas not addressed in this literature deserves more attention. Furthermore, Muhammad et al. analyzed various studies on weather and climate extreme events (WCEE), mainly involving the pre-, during, and post-disaster phases [5]. These studies concentrated on damage assessment, spatial scope, loss, and disaster management methods, with only a few exploring risk predictions. Compared to this paper, which also discusses these aspects, the emphasis here is more on the impact on the insurance industry. This paper is mainly related to the risk assessment of urban supply and demand imbalance affected by extreme weather, which overlaps with the work of this paper, but this paper focuses more on the impact on the insurance industry [6]. **错误!未找到引用源。**Then this work in this paper focuses more on the impact of the biological world on the population of a particular animal, which is not very similar [7]. This article also refers to the problem of weather affecting ship scheduling, and finds that time series analysis is also used in it, but it does not coincide with its research direction [8]. Similarly, when exploring whether rainfall intensity significantly affects the speed of interstate traffic, it can be found that extreme weather also poses a significant threat to transportation systems [9].

The paper examines the impact of extreme weather on the insurance industry, utilizing various methods due to the lack of existing research. Data on extreme weather occurrences in the United States and Africa were collected and analyzed, and future losses and insured populations were predicted using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. A break-even estimation model was used to establish baseline factors for insurance programs, guiding underwriting decisions based on risk tolerance and profitability goals. High-risk areas were identified and specific recommendations for risk management strategies were provided, including reinsurance and risk transfer.

A scoring model called CGDAM-WRIR was constructed to assess key educational areas across U.S. states, considering risk of extreme weather occurrence, culture, economy, landmarks, and history. Preservation recommendations were based on the final risk scores. Time trend analysis was conducted to identify peak occurrence periods for different extreme weather events, and the average damages of various weather extremes were ranked for an overall event impact analysis. Evaluation of Wynwood Walls in Florida was performed using insurance and protection models.

2 Method

2.1 Dataset Preparation

The data of this paper are all from the official websites of SRTM, WorldClim, etc. [10] 384 major disaster events from 1980 to 2011 and 7,082 disaster data were counted, including the number of deaths, the number of people affected, and the amount of economic loss. At the same time, this paper uses 340M elevation data to dematerialize the influence area. In this study, the stability of the autocorrelation coefficient (ACF) test data was selected, and the unstable data needed to be differentiated. Firstly, the processed data were normalized, and the ACF and partial autocorrelation coefficient (PACF) of the raw data and the differential data were calculated and visualized. The ACF shows the correlation of each moment in time with the previous moments, and if there is a clear cyclical or exponential downward trend on the ACF chart, then the time series may be non-stationary. The PACF shows the correlation of each moment to the previous moments, eliminating the influence of the others, and the PACF can help determine the parameters of the ARIMA model because it shows the pure autocorrelation of the sequence after removing the influence of the other moments. The higher the height of the ACF and PACF, the stronger the correlation, the abrupt truncation indicates that the time series is likely to be stationary, and the slow truncation indicates that differential processing may be required. Periodicity of ACF and PACF: If there are periodic fluctuations on ACF and PACF, it indicates that the time series may be non-stationary.

2.2 The Framework of the Proposed Approach

The methods employed in this study begin with AC-PAC-ARAIM, utilizing clustering algorithms to analyze regional catastrophic events, total losses, and casualties occurring in the United States and Africa from 1980 to 2020 using a risk assessment model. The SARIMA method is then employed to forecast potential losses over the next seven years and estimate annual losses and premiums. Subsequently, a profit-loss balance prediction model is developed to estimate monthly payout amounts. Following this, high-risk areas for specific extreme weather events are identified through geographic and event-type analyses, evaluating the intensity, frequency, and seasonal patterns of destruction. ArcGIS modeling is used to depict disaster risks in various locations. Next, scoring is conducted on various factors across U.S. states, and an AHP-TOPSIS model is constructed to provide protection recommendations. Finally, a composite model is utilized to forecast and score selected locations, offering suggestions for future development. Fig. 1 presents the main process of this project.

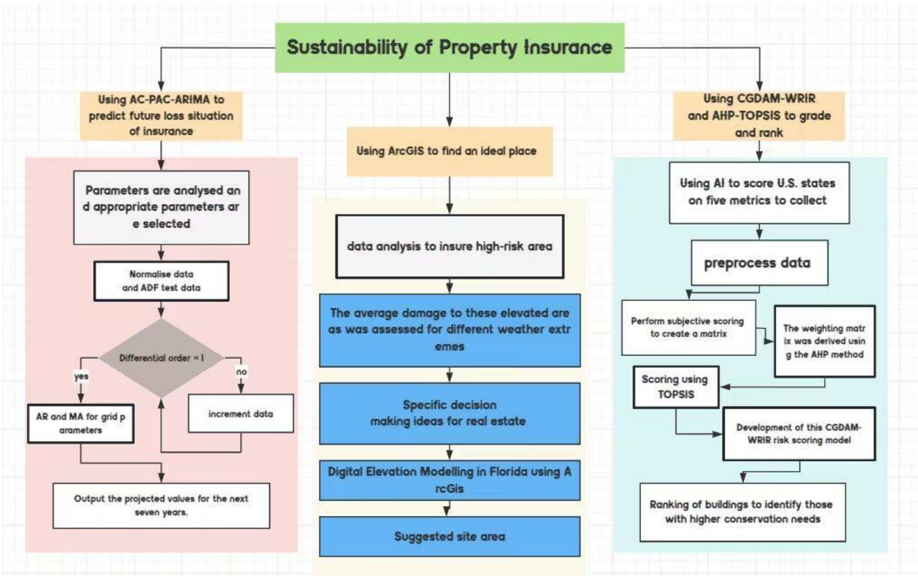

Fig. 1. The flow chat.

2.3 Implementation Details

SARIMA and AC-PAC-ARAIM. When developing contracts with different premiums for areas with different risk levels, this study developed the following program:

1) Develop scientifically sound risk assessment models - for each area, use more sophisticated models that may include multiple regressions to account for multiple factors, such as geographic features, building density, land use, etc. The risk assessment model for each area can be expressed as follows:

$$P(Extreme\,\text{weather event} \mid \text{area}) = \sigma(\beta_0 + \beta_1 \times Historical\,data + \beta_2 \times \text{Meteorological condition} + \beta_3 \times \text{Geographical characteristics} + \ldots\ldots) \tag{1}$$

2) Classify the model into different risk classes using clustering algorithms - Classify districts into different risk classes (e.g., low, medium, and high) based on the results of each district's risk assessment; this can be accomplished by setting different thresholds and using clustering algorithms.

3) Setting different premiums according to different risk classes - For each risk class, set a different Base Premium Rate (BPR), which indicates the base cost per unit of face amount; according to each risk class, adjust the BPR by an Adjustment Facto (AF) to adjust the BPR for each risk class to reflect risk differences. Specifically, the premium (P) can be expressed as:

$$P = BPR \times AF \tag{2}$$

4) Adjustment Factor Calculation - The adjustment factor can be determined by the probability of the output of the risk assessment model, or it can take into account other factors related to the level of risk; the calculation of the adjustment factor may

involve several parameters, such as：

$$AF = \alpha + \beta_4 \times P + \beta_5 \times other \text{ factors} \tag{3}$$

And then the SARIMA model, fully known as Seasonal Differential Autoregressive Sliding Average model, is designed to characterize the autocorrelation of a one-dimensional time series and to forecast the future, and it is improved on the ARIMA model by converting the non-smoothed time series into a smoothed time series, while transforming the dependent variable to return only the present and lagged values of its lagged and random error terms. The basic equation of the ARIMA model can be expressed in the following way:

$$\left(1 - \sum_{i=1}^{P} \varnothing_i L_i\right) \times (1 - L)^d y_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \tag{4}$$

The L lag operator acting k times on y_t will get the value before period k. Each component in the model has a specific role, θ_{i} are the autoregressive coefficients which are multiplied by the P prior values of the time series, θ_{i} are the moving average coefficients which are multiplied by the Q prior error terms of the model, and d is the number of differentiations the model needs to perform in order to ensure that the time series is smooth. To determine the parameters P, D and Q of the model, it need to base the autocorrelation coefficient and partial autocorrelation coefficient of the time series. These functions help us to visualize the correlation between the data and its independent correlation with other data points. The SARIMA model adds four seasonal parameters P,D,Q and s to the ARIMA model. P denotes the periodic autoregressive order, D denotes the periodic difference order, Q denotes the periodic moving average order, and s denotes the length of the season or cycle size.

Subject to expected profits (P), and the amount of compensation required for each individual (N), the specific enrollment costs for each individual can be adjusted to ensure that the company can cover the cost of compensation and realize the required profits. The following is one possible calculation:

Assuming that the specific enrollment cost for each individual is (C), the total premium-revenue is $M \times C$. You want to ensure that the company is able to achieve the required level of profit (P) while providing the insurance service, so you can calculate the specific enrollment cost for each individual by using the following formula:

$$C = k + \frac{P}{M} + \frac{N}{M} \tag{5}$$

The above formula has three components:

Base cost component (k): base premium rate paid per enrollee.

Expected profit sharing component (P / M): the expected profit is divided according to the number of participants M.

Amount to be compensated per person (N / M): the amount to be compensated per participant (N) is allocated to each participant.

the factors underlying the program were identified and the relevant formulas are as follows:

$$C = C_f + C_v \times Q \tag{6}$$

C denotes cost, C_f denotes fixed cost, $C_v \times Q$ denotes variable cost, C_v denotes variable cost per unit, Q denotes sales volume, and Q is the ratio of the number of policies sold to the number of policies.

$$C_c = r_c \times Q \times C_a \times \frac{1}{(1+i)^t} \tag{7}$$

$$r_c = r_z \times r_s \tag{8}$$

Total amount claimed = Claims rate × Number of policies × Average individual claim amount × Compound present value factor

Where i is the discount rate for the time value of money, and for simplicity of calculation, t = 1.

Sales Revenue = Average Unit Price * Number of Policies (excluding taxes) (10)

Let us

$$B = C + C_c + D \tag{9}$$

D is the profit, and later, for graphical convenience let D be 0 first to get $Q\times$ (reflecting the break-even through the number of policies).

CGDAM-WRIR and AHP-TOPSIS. The raw data were subjectively scored to create a matrix and the AHP method was used to derive a weight matrix M. The mth power of the product of each row was calculated to obtain an m-dimensional vector.

$$\overline{w}_i = \sqrt[m]{\prod_{j}^{m} a_{ij}} \tag{10}$$

Normalizing the vector to a weight vector gives the weights.

$$w_i = \frac{\overline{w}_i}{\sum_{j=1}^{m} \overline{w}_j} \tag{11}$$

Using weighting to multiply the source data by the resulting weights.

Normalize the raw data to obtain the norm matrix Y, where:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{n} x_{ij}^2}} \tag{12}$$

2）Assuming that is the indicator, is the corresponding weight coefficient, the positive and negative of each indicator of the positive indicator of the ideal weighted distance flat

Square sum:

$$f_i(w_1, w_2 \ldots w_n) = \sum_{j=1}^{n} w_j^2 (1 - r_{ij})^2 + \sum_{j=1}^{n} w_j^2 r_{ij}^2 \tag{13}$$

The results are more accurate when the distance is smaller, i.e., when constructing a multi-objective planning model. The Lagrange function formula is as follows:

$$F(\omega,\lambda)=\sum_{i=1}^{m}\sum_{j=1}^{n}\omega_j^2((1-r_{ij}^2)-\lambda(1-\sum_{j=1}^{n}\omega_j) \tag{14}$$

Let

$$\begin{cases}\frac{\sigma F}{\sigma w_j}=\sum\left(w_j(1-r_{ij})^2+r_{ij}^2\right)-\lambda=0\\ \frac{\sigma F}{\sigma\lambda}=1-\sum_{j=1}^{n}w_j=0\end{cases} \tag{15}$$

Solving for this gives that

$$w_j=\frac{\mu_j}{\sum_{j=1}^{n}\mu_j} \tag{16}$$

Included among these,

$$\mu_j=\frac{1}{\sum_{i=1}^{m}\left((1-r_{ij}^2)+r_{ij}^w\right)} \tag{17}$$

The objectives are ranked according to their superiority or inferiority Chengdu, and the distance between the objectives and the positive and negative ideal solutions is calculated:

$$S_i^*=\sqrt{\sum_{j=1}^{n}\omega_j^2 r_{ij}^2} \quad j=1,2,\ldots n \tag{18}$$

$$S_i^{\cdot}=\sqrt{\sum_{j=1}^{n}\omega_j^2 r_{ij}^2} \quad j=1,2,\ldots n \tag{19}$$

Calculate the relative closeness of each target:

$$C_i^{\cdot}=\frac{S_i^{\cdot}}{S_i^*+S_i^{\cdot}} \quad i=1,2,\ldots m \tag{20}$$

Finally, the advantages and disadvantages of each objective are ranked based on relative posting progress and the best result is selected.

To develop this risk scoring model, needed consider the following factors:

Probability of Damage (Q): the likelihood that a building will be exposed to extreme weather over a certain period of time. This can be calculated based on past event data.

Extent of Damage (A): this refers to the extent of damage suffered by the building at the time of the event. This depends on the structural strength of the building, its location and its environment.

Building Significance (C): This reflects the cultural, historical, economic and community value of the building to the neighborhood. An ACP-TOPSIS composite scoring model was developed to analyze this.

Thus, it can be defined the risk score K for building I as follows:

$$K=Q\times A\times C \tag{21}$$

This score can be used to rank buildings in order to identify buildings with a higher need for conservation.

Data Preparation: First it creates a hypothetical dataset containing 3 buildings. The information in this data set includes the probability of damage (Q), the potential damage (A), and the importance score (C). These data are obtained based on previous data, and assessment analysis.

Calculate the risk score: then utilize the risk score formula:

$$(K_i = Q_i \mathrm{v} \times A_i \times C_i) \tag{22}$$

Calculate the building score. This score will be used to quantify the risk level. Sorting and analyzing the results: the calculated buildings will be finally ranked to help decision makers to choose and rationalize the allocation of resources.

Table 1. The key mathematical notations.

Symbol	Description	Symbol	Description
BPR	Base Premium Rate	L	lag operator
AF	Adjustment Factor	$\emptyset_i$	Autoregressive coefficient
P	Premium; Profit	θ_i	
N	The amount that each person needs to compensate	d	Moving average coefficient
C	Specific insurance fees for each individual	P	Number of differences
K	Base cost component	D	Periodic autoregressive order
P/M	Expected profit sharing component	Q	Periodic difference order
N/M	Amount per person required apportionment portion	s	Periodic moving average order
C	Costs	Q	Periodic time interval
Cf	Fixed costs	A	Damage probability
Cv	Variable cost per unit	C	Potential damage probability
Q	Volume of production and sales	M	Importance score
D	Profit		Weighting matrix
I	Time value of money discount rate		

3 Results and Discussion

3.1 Loss Projections

According to the previous assumptions, it predict the expected loss for each year, and get the expected loss prediction for the next seven years, in the SARIMA modeling, it need to analyze the parameters first, select the appropriate parameters, first of all, carry out the ADF test to see whether the data is stable or not, and if it is stable, then the order of the difference will be 1, and then carry out a lattice parameter. It searches for the optimal parameter for AR and MA, and outputs the predicted value for the next seven years.

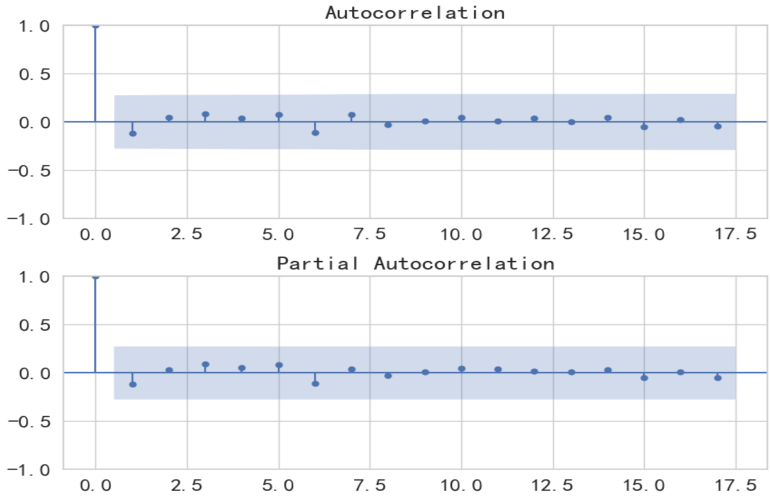

Fig. 2. Disaster prediction for the African region.

In this study, ACF was chosen to test the stability of the data, and the unstable data needed to be differenced. The outcome is represented in Fig. 2. First, the data were normalized after processing, and the ACF and PACF were calculated and visualized for the original and differenced data. The ACF shows the correlation of each moment with the previous moments. The PACF shows the correlation of each moment with the previous moments and can help to determine the parameters of the ARIMA model because it shows the pure autocorrelation of the series after removing the influence of other moments. Based on this, use the ARIMA time series model to make forecasts of expected compensation losses for different regions for each year.

Specifically, after predicting the probability of the disaster occurring, it is also necessary to predict the damage expected to result from the disaster, and an intuitive way to deal with this is to directly predict the expected number of casualties or the expected damage locally at that time period. An ARIMA model is used to predict the damage caused by an extreme weather event over the next seven years, with results as shown in Table 2.

Table 2. Results of damage projections due to extreme weather (Africa)

	Year	Projected losses
50	2024	2.354257e+09
51	2025	2.487192e+09
52	2026	1.915864e+09
53	2027	2.190285e+09
54	2028	2.143516e+09
55	2029	2.115999e+09
56	2030	2.139755e+09

Predictions are made for total losses in the U.S. in Table 3, so it is trained by day and then predicts the data for the coming month, and for the predictions, the same can be done for the estimation of premiums for each month. Again, prior to this, it performed plots of partial autocorrelation and coefficient of coefficient of correlation to determine the smoothness of the time series data in Fig. 3 and to calculate the parameters of the ARIMA model.

Table 3. Projected losses in US

	Year	Projected losses
275	19950101	355689.782504
276	19950102	138128.778806
277	19950103	334210.259428
278	19950104	164296.496380
279	19950105	311325.418672
280	19950106	183958.065027
281	19950107	294273.362622
282	19950108	198726.241089
283	19950109	281482.406979
284	19950110	209804.906131
285	19950111	271886.860125

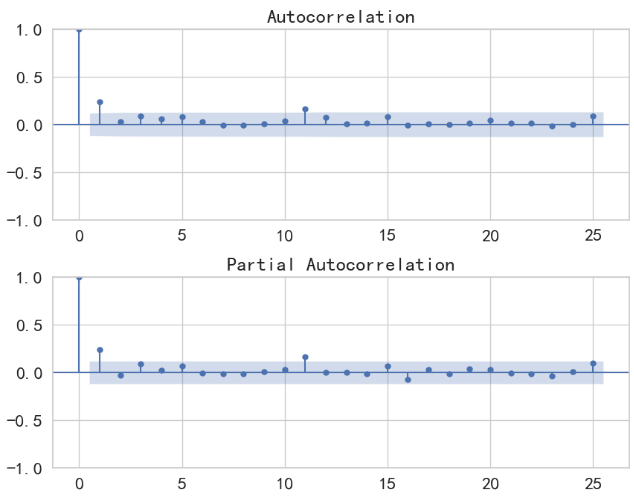

Fig. 3. Disaster prediction for the US region.

3.2 Break-even Prediction Model Solving

Table 4 lists experts who believe that in the process of insurance claims, 5% of them will be paid for losses, i.e. the claim rate is 5%. Let's assume that the fixed cost of the company is 1000, and according to our projections, the loss in the US in 2024 will be 118,847.18 million, the number of insured will be 152,745 million, and the number of Americans will be 334,233 million, so it expected that 54,313.83 million dollars will be needed to pay out compensation in 2024, and when the insurance company expects to make 10 billion dollars in revenues, the cost per policy will be 421.05 and the projected payout per policy is $7,115.628.

Table 4. Benchmarking Factors for U.S. Insurance Programs

Indicator Baseline (self-defined, reasonable)	Indicator Baseline (self-defined, reasonable)
Expected claims rate	0.05
Average cost per policy	421.05
Average amount per claim	7115.628
Time value of money discount rate	10%
Fixed costs	1000

According to model projections in Table 5, Africa's projected losses in 2024 are $2,354.257 million, the number of insured people in Africa is projected to be 531 million, and the number of people in Africa is 1,417 million, with a projected need for compensation of $882.2 million in 2024, and a projected payout of $6,156.348 per policy when projected revenues are $100 million, at a cost per policy of $253.07 per policy.

Table 5. Benchmarking factors for insurance programs in Africa.

Indicator Baseline (self-defined, reasonable)	Indicator Baseline (self-defined, reasonable)
Expected claims rate	0.05
Average cost per policy	253.07
Average amount per claim	6156.348
Time value of money discount rate	10%
Fixed costs	1000

3.3 Damage assessment

Still taking Florida as an example, this essay built a digital elevation model of Florida and hospitals, malls, subways, and input the latitude and longitude where extreme weather has occurred in recent years (Fig. 5); Then extracted the distance data from the occurrence of extreme weather, hospitals, malls, and subways, and the extreme weather portion of the model is shown here; Then built a slope model and weighted the distance data to score it, resulting in the final map (Fig. 4) of the proposed sites, with the darker the color the less the site is recommended.

Fig. 4. Digital High-Level Modeling of Extreme Weather Latitudes, Longitudes and Special Landmarks

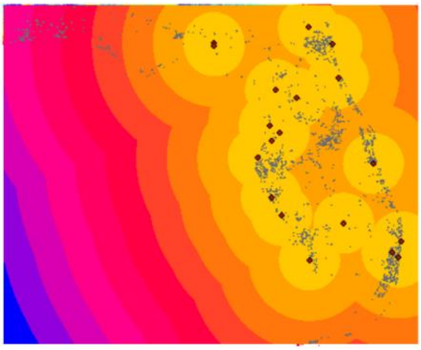

Fig. 5. Proposed site map

Table 6 presents the weights of all aspects occupied. Since the mean value of the data scores is 22.2222222222222222227, if the resulting score is greater than 22.2222222222222222227 more measures of protection are required, and if it is less than that protection is provided on a case-by-case basis.

Table 6. AHP-derived weighting table

Disaster	Culture	Landmark	history	economic
37.773%	15.237%	5.940%	9.002%	31.958%

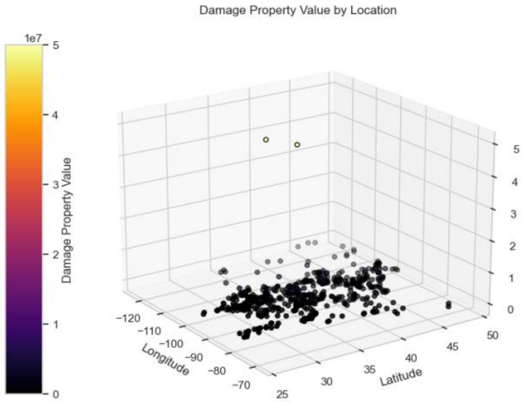

Fig. 6. Damage scores at different latitudes and longitudes.

The first step is to understand the frequency of local high-risk extreme weather events and the extent of damage, in the U.S., for example, tornadoes are the most common extreme weather events, and further research has shown that tornadoes are most frequent in Texas, and most frequent in Nebraska, Florida, Iowa, and Kansas. and KANSAS states. In addition, the Fig. 6 presents that a property damage-latitude and longitude model was built to visualize the relationship between geographic location and property damage, which shows that there are very few areas with high property damage values, distributed between 40 and 50° latitude, and most of the areas have low property damage values, with the highest concentration of distributions between 30 and 50° latitude, and -80 and 110° longitude.

3.4 Risk scores for key education areas

In order to ensure the long-term stability of the community, it conducted a building risk assessment of the areas most affected by climate impacts, quantified the building risks, and developed a risk scoring model to help community leaders make the right decisions. An ACP-TOPSIS composite scoring model was developed to analyze this. Thus it is possible to define the risk score K for building I. This score can be used to rank buildings in order to identify buildings with a higher need for conservation.

Thereafter, in Fig. 7, for the Focused Education Region risk scores, Texas remains significantly higher than the other regions. The risk scores for the remaining regions are more evenly distributed, with NEBRASKA having the highest score, followed by Florida and LOWA.

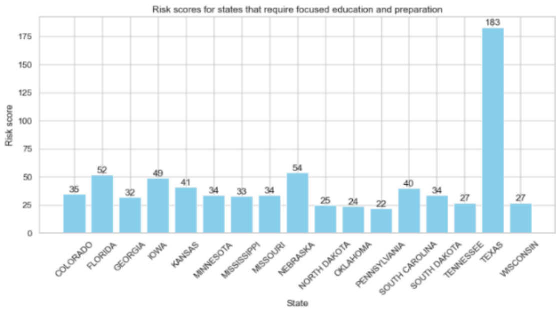

Fig. 7. Risk screens in key educational areas.

3.5 Analysis of incident trends

After time trend analysis in the Fig. 8, it was found that the most common seasons for hailstorms are spring and summer, more common in fall, and rare in winter; the most common season for thunderstorms is summer, followed by spring, fall, and rare in winter; and the most common season for tornadoes is summer, followed by spring and fall. Different disaster response measures should be taken for different seasons, for example, the impact of thunderstorms on property resources and human resources should be highly emphasized in summer. And the response to hail should focus on spring and summer.

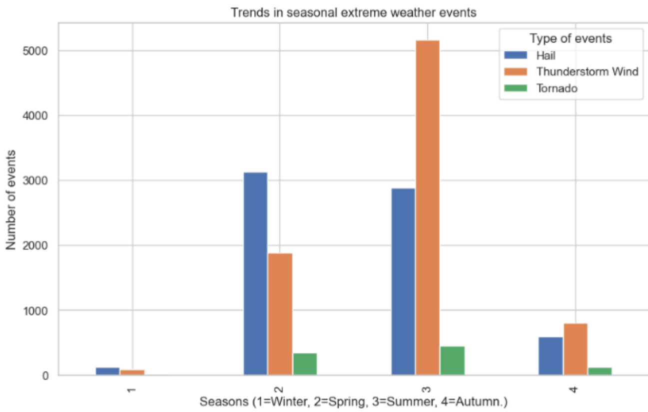

Fig. 8. Frequency of different extreme weather events

4 Conclusion

In order to solve the problems caused by the increasingly severe extreme weather events, it established comprehensive models for case studies, including: AC-PAC-SARIMA-based loss prediction model, decision-making assessment model, protection model for buildings in the community, and landmark value assessment model. Taking the U.S. region and Africa as examples, this study conducted statistical analysis of disaster events and built a prediction model to forecast the future trend of disasters; it also classified disaster levels and explored the relationship between geographic location factors and the risk of disasters according to latitude and longitude. Also, the model has some drawbacks. First, this model performs well in the data in this example, but the model may lose its ability to generalize due to overfitting of the data and may be affected by other factors in reality, resulting in mathematical relationships that are not applicable. Then, the model does not have access to all the data for the required indicators, which inevitably have missing values. Although this paper has dealt with the missing values, the accuracy of the model is still affected. Also, in the future this model can be improved in some aspects such as adding more data to increase the model applicability.

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